Robustness of Air Transport Networks in the World: Case of Turkey against USA and China

"A Closer Look to Countries Air Transport Networks"

Emir Kılkıl

ekilkil@sabanciuniv.edu

Cenk Eligüzeloğlu

ecenk@sabanciuniv.edu

Sadi Çelik

sadicelik@sabanciuniv.edu

1. Abstract

In this paper, various airline network datasets will be thoroughly examined in order to determine network robustness of different countries. Some countries that will be selected, will be represented as individual networks where each city with an airport will be nodes of that network. At the same time, flight information between any airports will represent undirected and unweighted edges between these nodes. Various amounts of different efficiency metrics will be suggested to investigate the robustness of individual networks. Between any nodes, edges can be represented by any airlines, there just need to be a flight occurring between those two airports. While measuring the robustness of air transport networks, there will be two types of attacks. First type will be targeted attacks in which a targeted important airport node will be removed from the network. This importance will be determined according to the metrics that will be suggested during the paper. Targeted attacks will continue until the collapse of the network. Second type of attacks will be random attacks in which targeted airports will be selected randomly in order to simulate various failures of airline traffic such as weather conditions, flight time delays, mechanical failures, etc. The effect of removal of these airports to the robustness and efficiency of the network will be inspected.

2. Introduction

Nowadays, with the increase in movement of passengers and cargo by aircraft such as airplanes, air transportation has become the primary means of common traveling method. According to the International Air Transport Association (IATA), in 2017, airlines carried 4.1 billion passengers globally. This value increased by 7.3% over 2016, which represented an additional 280 million trips by air between 2016 and 2017[1]. As its importance in transportation methods, air transportation also provides a huge infrastructure for countries both domestic and global economies. This statistic shows that more than half the population of the entire world has been carried around the world via air transport. That is why, any misfortune on air transportation can cause very negative results. These negative results can be originated from various failures on air transportation traffic such as weather conditions, flight time delays, mechanical failures, etc. In order to examine and simulate these effects, air transport networks of different countries will be taken into consideration. With different dynamics and features of each country, negative effects on the air transport network would cause a different challenge. For this investigation, countries will be represented as individual networks where each city with an airport will be nodes of that network. At the same time, flight information between any airports will represent undirected and unweighted edges between these nodes. Various amounts of different efficiency metrics will be suggested to investigate the robustness of individual networks. Between any nodes, edges can be represented by any airlines, there just need to be a flight occurring between those two airports. While measuring the robustness of air transport networks, there will be two types of attacks in which misfortunes mentioned above will be simulated. First type will be targeted attacks in which a targeted important airport node will be removed from the network. This importance will be determined according to the metrics that will be suggested during the paper. Targeted attacks will continue until the collapse of the country's air transport network. Second type of attacks will be random attacks in which targeted airports will be selected randomly in order to simulate various failures of airline traffic such as weather conditions, flight time delays, mechanical failures, etc. The effect of removal of these airports to the robustness and efficiency of the network will be inspected. Countries presented in this paper will be the Republic of Turkey, United States of America and the People's Republic of China. The effect of key airports of these countries to the robustness of the country's air transport network will be examined and Turkey's air transport network will be compared against USA's and China's.

[1] "Air Transport." Air Transport - an overview | ScienceDirect Topics. Accessed May 25, 2021. https://www.sciencedirect.com/topics/engineering/air-transport.

3. Methodology

3.1. Data Description

OpenFlights is a tool that lets people map flights around the world, search and filter them in all sorts of interesting ways, calculate statistics automatically, and share flights and trips with anyone in the entire world. It's also the name of the open-source project to build the tool. OpenFlights's airport, airline and route data contains over 10,000 airports, train stations and ferry terminals, 5888 different airlines and 67663 routes between 3321 airports on 548 airlines from all over the world[2]. From these datasets, every flight from Turkey, USA and China are sorted out and each country formed an airport transportation network. In these networks, often there were more than one flight between two cities due to the number of airports in those cities. For example, Istanbul had three different airports thus an example route between Istanbul and Izmir could have existed in the data three times. This was very common in metropolitan cities such as Istanbul, Atlanta and Beijing. That is why every city is identified as one single node and any flight by any airline company from one city to another is considered as an edge between these two cities. In order to make this happen, airport and the route datasets of OpenFlights are combined together and obtained a dataframe from it containing source and destination airports, source and destination airports International Air Transport Association (IATA) values, source and destination cities for each network as it can be seen in the Figure 3.1.1. Dataframes for USA and China can be observed from Table a-1 and Table a-2 in the appendix a.

source_airport_iata	destination_airport_iata	source_airport_name	source_aiport_city	destination_airport_name	destination_aiport_city
ADA	IST	Adana Airport	Adana	Istanbul Airport	Istanbul
ADB	IST	Adnan Menderes International Airport	Izmir	Istanbul Airport	Istanbul
AYT	IST	Antalya International Airport	Antalya	Istanbul Airport	Istanbul
BJV	IST	Milas Bodrum International Airport	Bodrum	Istanbul Airport	Istanbul
DIY	IST	Diyarbakir Airport	Diyabakir	Istanbul Airport	Istanbul
DLM	IST	Dalaman International Airport	Dalaman	Istanbul Airport	Istanbul
ERZ	IST	Erzurum International Airport	Erzurum	Istanbul Airport	Istanbul
EZS	IST	Elazığ Airport	Elazig	Istanbul Airport	Istanbul
GNY	IST	Şanlıurfa GAP Airport	Sanliurfa	Istanbul Airport	Istanbul
GZP	IST	Gazipaşa Airport	Alanya	Istanbul Airport	Istanbul
GZT	IST	Gaziantep International Airport	Gaziantep	Istanbul Airport	Istanbul
IST	ADA	Istanbul Airport	Istanbul	Adana Airport	Adana
IST	ADB	Istanbul Airport	Istanbul	Adnan Menderes International Airport	Izmir
IST	AYT	Istanbul Airport	Istanbul	Antalya International Airport	Antalya
IST	BJV	Istanbul Airport	Istanbul	Milas Bodrum International Airport	Bodrum

Figure 3.1.1: Turkey Air Transport Network

[2] "About." OpenFlights. Accessed May 25, 2021. https://openflights.org/about.

3.2. Robustness Assessment

As it is introduced in the introduction part of this paper, the main aim is to try successful simulations on countries' air transport networks and observe what will happen in case of various failures on airline traffic such as weather conditions, flight time delays, mechanical failures, etc. or which key cities are most important for countries' networks. In real life, failures like weather conditions or airline traffic can happen to any airport in any city or country regardless of the importance of that airport inside the air transport network. These kinds of events are more likely to occur randomly. On the other hand, the target of an incident like a terrorist attack would have been more specific in order to cause a huge impact. To simulate these different events, two attack types will be introduced; random attacks in which removal of airports will be random and targeted attacks in which removal of airports may be selected according to degree, betweenness-centrality, closeness-centrality; in short according to their criticality.

"Node-degree distribution" of real networks such as the air transport networks of countries often show a skewed node-degree distribution in which most nodes have only few links, on the other hand, there exist some nodes which are extremely linked[3]. The translation of this network science notion into the air transport network observed in this paper would be that some airports will have many routes between other cities, thus their degrees would be very high. At the same time, some other airports will not be as busy as the airport nodes who have high degrees; thus these airport nodes will have less routes between other cities, meaning lower degrees. If an airport receives a targeted attack according to its node degree importance, most possibly more edges in the network will be affected and greater damage will be taken.

"Betweenness-centrality" is a widely used phenomena in network science that captures a node's role in allowing information to pass through itself as a bridge from one part of the network to the other[4]. For example, let's consider Istanbul in the air transportation network of Turkey as it is shown in Figure 3.2.1. Istanbul is a critical node that connects most of Turkey's airports and from Istanbul most of Turkey's airports in other cities are reachable. This makes Istanbul's betweenness-centrality measure high, 0.65, as it is close to 1. Thus, Istanbul is very important for the flow of air transportation through Turkey's network. For other cities' betweenness-centrality measurement in Turkey Figure 3.2.2 can be observed. This is actually what betweenness centrality captures. Technically, it measures the percentage of shortest paths that must go through the specific node. Despite the fact that computation of betweenness-centrality is quite complex, the NetworkX network library in python is computing

[3] Scholz, Matthias. "Node Degree Distribution." Network science: node degree distribution. Accessed May 27, 2021. http://www.network-science.org/powerlaw_scalefree_node_degree_distribution.html.
[4] "Betweenness Centrality." Betweenness Centrality - an overview | ScienceDirect Topics. Accessed May 27, 2021. https://www.sciencedirect.com/topics/computer-science/betweenness-centrality.

it quite easily for a given network. The important thing to know is that betweenness is a measure of how important the node is to the flow of information through a network, thus targeted attacks may utilize this measure. USA's and China's air transportation networks' Gephi representation is in the appendix b as table b-1 and b-2 in order to see a representative view of their cities betweenness-centrality.

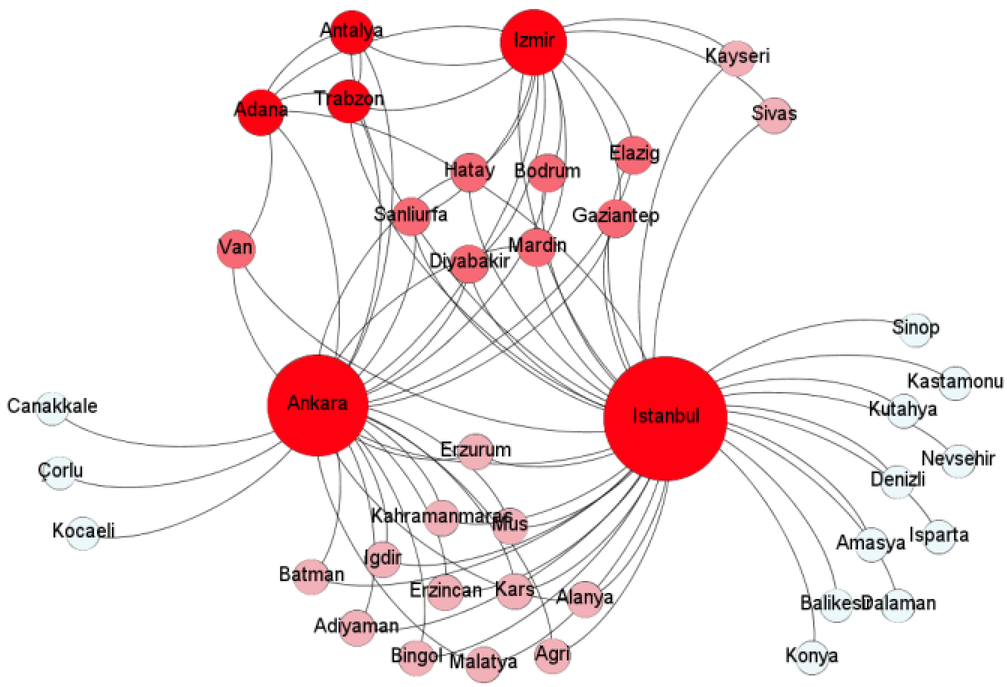

Figure 3.2.1: Turkey Air Transport Network Representation on Gephi

"Closeness-centrality" measurement in network science measures each node's position in the network via a different perspective from the other network metrics, capturing the average distance between each node and every other node in the network. Assuming that an airplane in an air transport network for example can only fly to or through from its source nodes existing connections, a high closeness centrality will mean that the source airport (node) is directly connected or "just a hop away" from most other airports in the network. In contrast, nodes in very peripheral locations may have low closeness centrality scores, indicating the high number of hops or routes they need to fly over in order to reach a distant airport in the network[5]. This metric should be considered as a "distance" score. Another big city of Turkey, Ankara, has a high closeness centrality degree of 0.7 which is close to 1 meaning that most airports in Turkey are in close reach of Ankara. Other cities' closeness centrality measurement in Turkey can be observed from Figure 3.2.2.

[5] "Closeness Centrality." Closeness Centrality - an overview | ScienceDirect Topics. Accessed May 27, 2021. https://www.sciencedirect.com/topics/computer-science/closeness-centrality.

All these three measurements together define the "***criticality***" of an airport inside an air transport network. According to the criticality of the airport, the targeted attack type picks important cities as targets and tries to damage the network as much as possible. Criticality measurements for Turkey can be observed from below Figure 3.2.2 and other countries, appendix c contains Figure c-1 and c-2 for USA and China respectively.

	Degree	Betweenness Centrality	Closeness Centrality
Istanbul	37	0.652564	0.930233
Ankara	28	0.304487	0.769231
Izmir	14	0.036538	0.606061
Adana	6	0.001282	0.540541
Trabzon	5	0.000000	0.533333
Antalya	5	0.000000	0.533333
Mardin	3	0.000000	0.519481
Hatay	3	0.000000	0.519481
Van	3	0.000000	0.519481
Gaziantep	3	0.000000	0.519481
Sanliurfa	3	0.000000	0.519481
Elazig	3	0.000000	0.519481
Diyabakir	3	0.000000	0.519481
Bodrum	3	0.000000	0.519481
Bingol	2	0.000000	0.512821

Figure 3.2.2: Turkey's cities criticality measurements

Apart from these mentioned measurements used for the targeted attack types, random attack types only depend on "***randomness"***. This attack type is mainly to simulate events such as weather conditions and air traffic delays etc. and it is regardless of any criticality measurement of an airport. Every airport in a country's air transportation network is equally likely to be selected and removed from the network. Also in random attack type, 20% of airports in a country's network is targeted, and after the removal of this 20%, the effect of losses of these airports are observed. The reason behind this percentage is actually very trivial, for example the effect of removal of 10 airports from Turkey's air transport network will be much harsher than 10 airports removal from USA's air transport network. The number 10 is a major number of airports for Turkey while it is comparably insignificant for USA.

3.3. Robustness Assessment Indicators

3.3.1. Indicators reflects the targeted attacks effect

As it is explained in the part 3.2 Robustness Assessments, in targeted attack type different metrics are used in order to choose a specific targeted airport from the network and remove it to observe its effects over the air transport network of a country. After this process, the aftermath of these removals over networks should also be assessed in the light of several metrics such as average degree on networks and largest degree of the network.

"***Average degree of the network***" is simply the average number of edges per node in the network. It is relatively straightforward to calculate by adding up the degrees of all the nodes remaining in the network and dividing it by the number of nodes. It is simply to measure the effectiveness of the connections between airports. Since targeted attack type aims at critically important airports, it is presumed that initially high average degree of the network will decrease more and more by the continuous attacks and since the network loses its critically important airports, each node's degree will decrease as the average degree of the network. This is one of the aims of the targeted attack type to decrease.

"***Largest degree of the network***" is for the measurement of the airport which contains the largest amount of routes after the attacks. Largest degree of the network is another measurement that aims to decrease by the targeted attack type since as critically important airports are removed, it is presumed that remaining airports' number of connections will decrease compared to the initial number.

In the end, with the decrease in the two measurements mentioned above, the expected behaviour for a network is it to divide into smaller clusters since some routes connections between airports may become disrupted. Istanbul city for example in Turkey's air transportation network is a critical city that has connection routes between most of the airports in the country and after the removal of Istanbul, some airports or a group of airports may become unavailable. Since the targeted attack will go on until there are no more routes in the air transport network. In this situation, the aim is to find how many airports it takes to remove from the network in order to completely collapse the network and no flights between any city will be possible. When there are no more flight options left, this may result in huge negative effects on countries' economic and transport infrastructure for example as it is stated in the introduction part.

3.3.2. Indicators reflects the random attacks effect

As it is explained in the part 3.2 Robustness Assessments, in random attack type every airport is equally probable to be removed from the network and 20% of airports in a country's network is targeted. After the removal of this 20%, the aftermath of these removals over networks should also be assessed in the light of several metrics such as largest connected component and global efficiency.

"***Largest connected component"*** of an undirected network is a maximal set of nodes such that each pair of nodes is connected by a path. Connected components form a partition of the set of network nodes, meaning that connected components are non-empty, they are pairwise disjoints, and the union of connected components forms the set of all nodes. Equivalently, we can say that the relation that associates two nodes if and only if they belong to the same connected component is an equivalence relation, that is it is reflexive, symmetric, and transitive. In real undirected networks, it is found out that typically there is a large component (the largest component) that fills most of the network - usually more than half and not infrequently over 90% - while the rest of the network is divided into a large number of small components disconnected from the rest[6]. After the 20% loss of its airports randomly, the situation of the network is measured with this metric. A big size of the largest connected network means that most of the air transport network is preserved and there are still lots of connected airports in the network. This suggests that this network is sustaining strongly against random anomalies and delays. On the other hand, the small size of the largest connected network means even the biggest connecting set of airports also contains a small number of the airports that exist in the network. That implies that these random anomalies and delays were very effective over the network and the network could not sustain very strongly.

Also another metric is defined in order to measure how efficient a network is. This efficiency is stated as the "***Global efficiency***" and it basically is the reciprocal ratio of the shortest distance dij between node i and node j in a network. When node i and node j are unconnected, dij = +∞ , so 1/dij = 0. For the whole network, the mean value of efficiency between all nodes will construct the global efficiency. When a flight occurs from a certain node towards another node, a shorter path length indicates a higher global efficiency for that flight. For example if the average shortest path between two airports in a network is 2, then this indicates that the global efficiency of the network is about 0.5[7]. After the random attacks and the gradual loss of the 20% of the airports in the network, the change in the global efficiency

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[6] Connected Components. Accessed May 27, 2021. https://www.sci.unich.it/~francesc/teaching/network/components.html.

[7] Chen, Yu, Jiaoe Wang, and Fengjun Jin. "Robustness of China's Air Transport Network from 1975 to 2017." Physica A: Statistical Mechanics and its Applications 539 (2020): 122876. https://doi.org/10.1016/j.physa.2019.122876.

will indicate how much capability the network lost. A high global efficiency of course reflects a positive impression which implies that after these random cuts of the airports, still reaching from an airport to another is quite short in the network. In contrast, a low global efficiency is a negative impression which implies that after these random losses, reaching from an airport to another in the network becomes harder and longer.

4. Results

Before examining the results of both random and targeted attack types over the air transport network of countries, the difference of the effect of the same attack over different countries should be discussed. As it is shown in the Figure 3.2.1 and figures b-1, b-2 in the appendix b, air transport network complexities of the countries are not the same. While the USA's and China's air transport network has many airports, many routes between each other; Turkey's network does not contain the same richness. As a result of this, the burden of Turkey's network is over three large cities - Istanbul, Ankara, Izmir - and any unavailability of airports in these cities will majorly cripple the air transport network of Turkey. On the other hand, because of the high number of airports and routes, USA's and China's have more alternative airports which connect most of the network through itself. USA has 4 major and 5 sub major airports - major airports are Atlanta, Chicago, Dallas-Fort, Denver and sub major airports are Charlotte, Detroit, Houston, Las Vegas, Washington - and China has 5 major and quite a lot sub major airports - major airports are Beijing, Chengdu, Guangzhou, Shanghai, Xi'an and sub major airports are Changcha, Hangzhou, Guiyang, Nanjin, Wuhan, ... - . This makes USA's and China's air transport network much more durable to any unavailability that occurs because they contain more alternatives for their hub cities.

In Figure 4.1, the results of 5 different random attacks on "***Turkey's Network***" can be observed. As it is stated on the part 3.3.2, random attacks only remove 20% of the network's airports. Because of the random nature of this attack type, the simulation is repeated 5 times in order to observe the removal effect of different cities. In the figure, each row represents another attack and the change in size of the largest connected component (LCC) is on the left while the change in global efficiency can be observed on the right. In the first row, 4th - although it is actually 5th removal numbers starts from 0 - removed city was Istanbul and with the removal of this node LCC measurement of the network quickly plumbed. Also, since a lot of direct flights over Istanbul to most of the airports are lost, average shortest paths between nodes are increased which results in decline in global efficiency. In the second and third rows, the jackpot of removal from the network hit cities like Igdir, Bingol, Agri and etc. whose degrees are 1 or very low. Thus their removals did not cause a steep decline as it was the case with Istanbul. Also, because they were nodes in the long border of the network, most probably their shortest path length was high and their removal actually increased the global efficiency of the whole network. In fourth and fifth rows, one of the removed cities were Izmir and Ankara respectively. These two cities are also among the largest hubs of Turkey's air transport network and that is why they caused a steep decrease similar to Istanbul in the first row although not as big as Istnabul. Respectively the global efficiency also decreased in similar manner between Izmir and Ankara as their degrees are similar but again this decrease was not as much as it was in Istanbul.

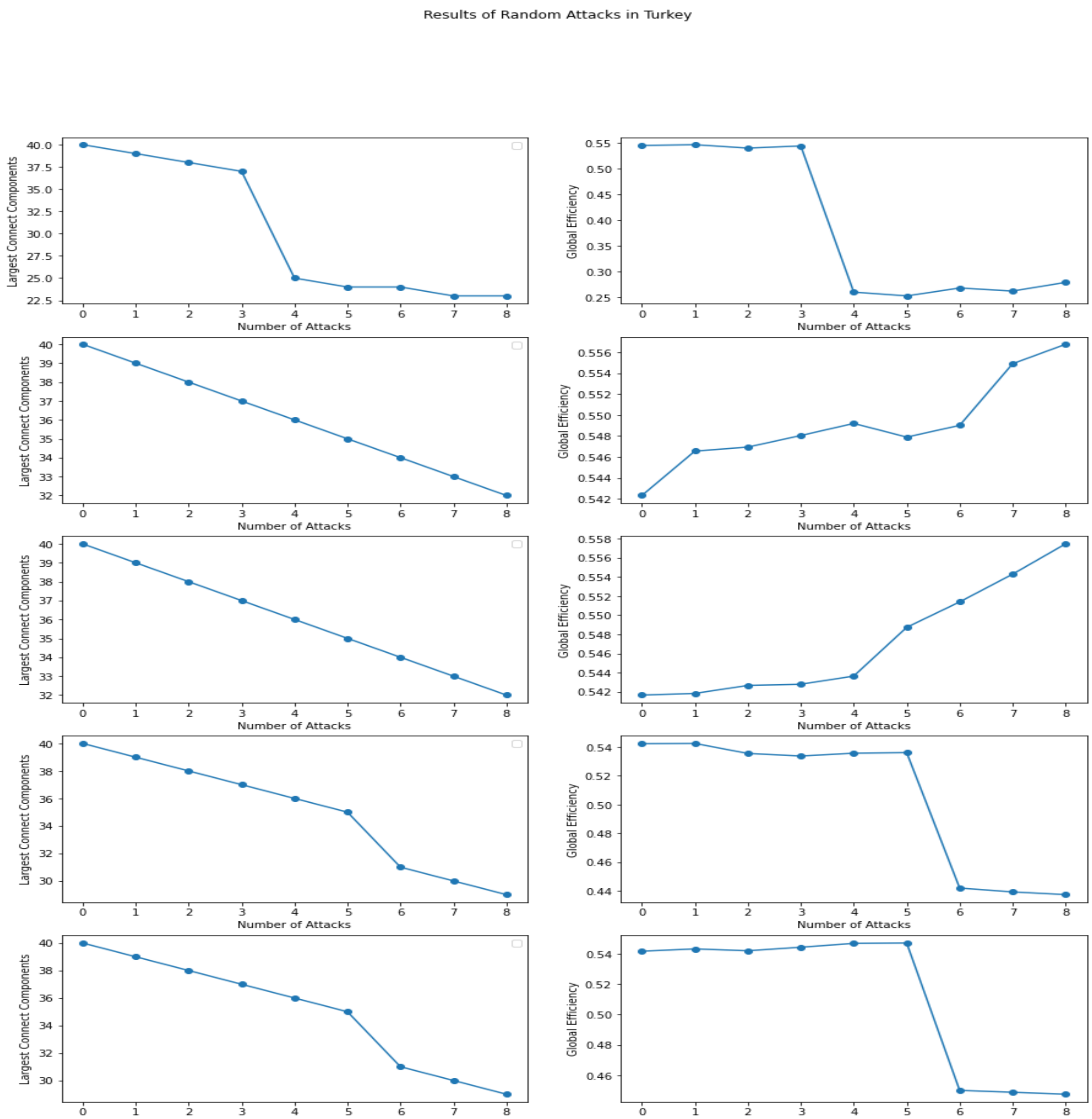

Figure 4.1: Random Attacks Results on Turkey's Air Transport Network

In Figure 4.2, the results of 5 different random attacks on "***USA's Network***" can be observed. As it is stated on the part 3.3.2, random attacks only remove 20% of the network's airports. Because of the random nature of this attack type, the simulation is again repeated 5 times in order to observe the removal effect of different cities. As it is with Turkey's network, each row on the figure represents another attack and the change in size of the largest connected component (LCC) is on the left while the change in global efficiency can be observed on the right. In the third and fifth rows, 7th and 22th removed cities were Atlanta and Dallas. With the removal of these nodes LCC measurement of the network quickly plumbed. As it is discussed briefly in the beginning of the result section, the difference between Turkey's network and USA's network is clearly observable in the 3rd row. Despite the removal of Atlanta, global efficiency only dropped for a little bit. This shows that average shortest path distances were not affected severely by this loss and managed to reach a lot of airports through different hubs with more or less the same number of steps. In contrast, the removal effect of Dallas was much more severe as it is seen in the fifth row. In the first, second and fourth rows, removed cities are not the major cities of the USA but instead sub major cities such as Washington and Houston or cities with very low number of connections such as Larsen Bay and Kodiak. Removal of these cities also decreased the LCC measurement of the network and lowered the global efficiency but this decrease was rather smoother than the removal of major cities. As a result, the network survived rather better in such cases.

In Figure 4.3, the results of 5 different random attacks on "***China's Network***" can be observed. As it is stated on the part 3.3.2, random attacks only remove 20% of the network's airports. Because of the random nature of this attack type, the simulation is again repeated 5 times in order to observe the removal effect of different cities. As it is with Turkey's network, each row on the figure represents another attack and the change in size of the largest connected component (LCC) is on the left while the change in global efficiency can be observed on the right. In the first row, 17th removed city was Guangzhou and with the removal of this node LCC measurement of the network quickly plumbed. Again, the difference between Turkey's network and China's network is clearly observable in the 1st row. Despite the removal of Guangzhou, global efficiency only dropped for a little bit. The drop looks very steep but if the values on the y-axis is examined, it only dropped from 0.5 to 0.465. This shows that average shortest path distances were not affected severely by this loss and managed to reach a lot of airports through different hubs with more or less the same number of steps. This success is directly related to the number of different alternative hubs that exist in China's air transport network. In the second, third and fourth rows, removed cities are again sub major cities such as Hangzhou, Wuhan or cities with very low number of connections such as Jinzhou and Chaoyang. Removal effect of these cities was rather smooth compared to major cities. As a result, the network survived better in such cases.

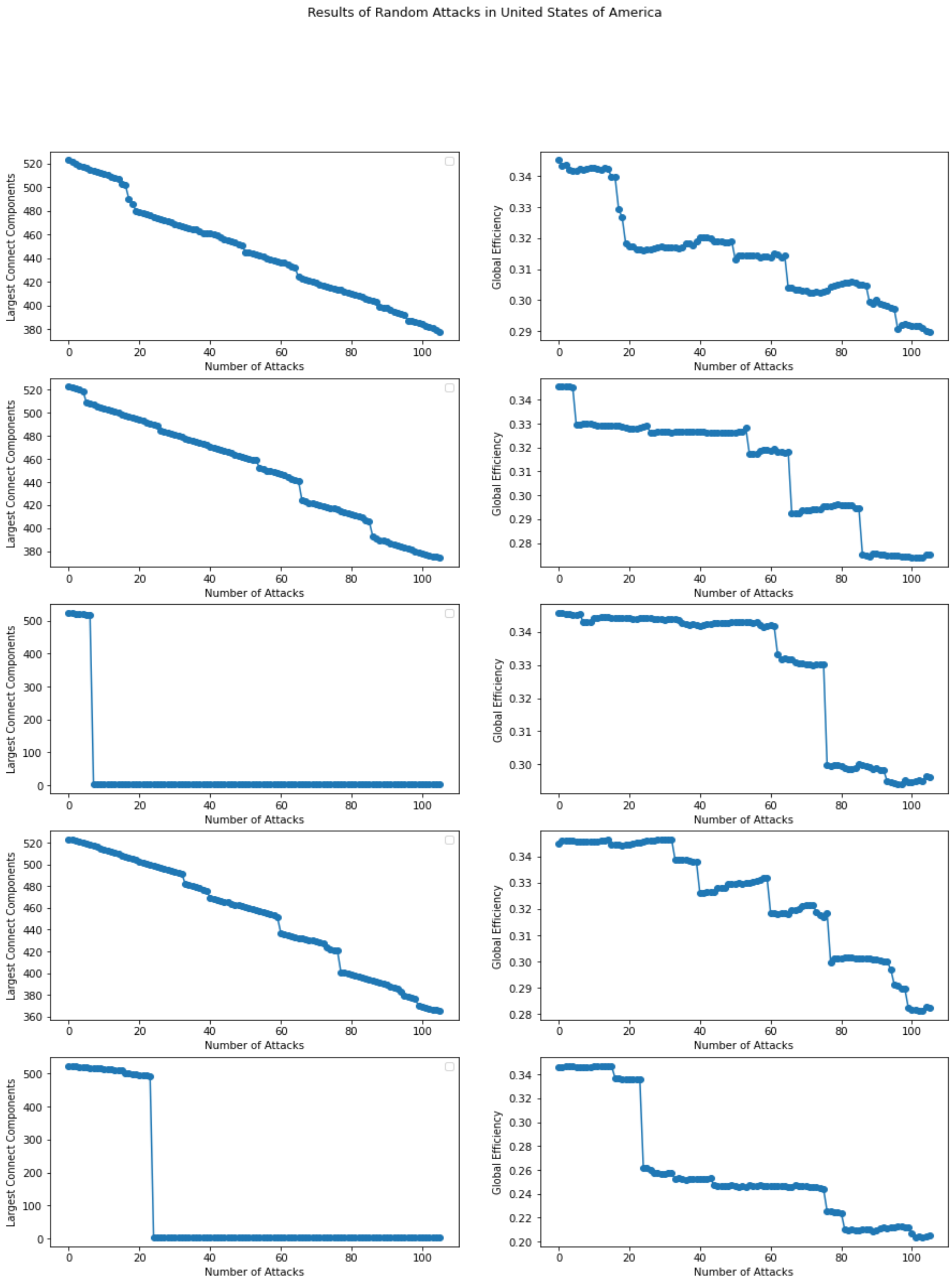

Figure 4.2: Random Attacks Results on USA's Air Transport Network

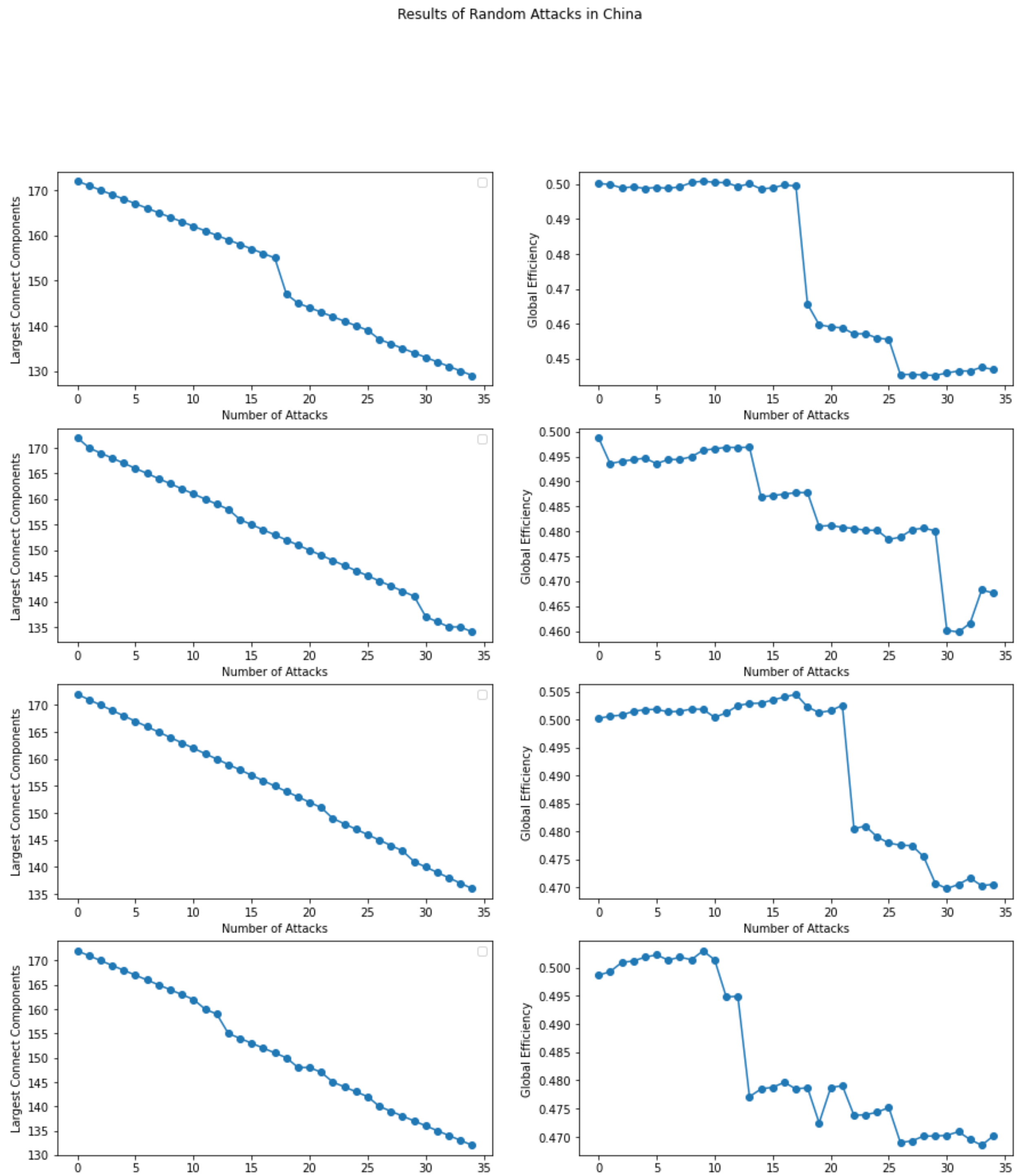

Figure 4.3: Random Attacks Results on China's Air Transport Network

In Figure 4.4, the results of the targeted attacks on "***Turkey's Network***" can be observed. As it is stated on the part 3.3.1, targeted attacks will step by step remove the most critical city and continue until there are no more routes left. In the figure, the change in average degree in the network is on the left while the change in the largest degree of the network can be observed on the right. In each removal, as expected these two measurement metrics keep decreasing. Initially, Turkey's air transport network had 41 cities and 80 routes in between them and in order to remove all the edges in the network, only 5 cities was enough. After the removal of Istanbul, Ankara, Izmir, Adana and Trabzon, the network completely collapsed. In case of a terrorist attack for example as this simulation tries to simulate, attacking only 12% of the network will be enough.

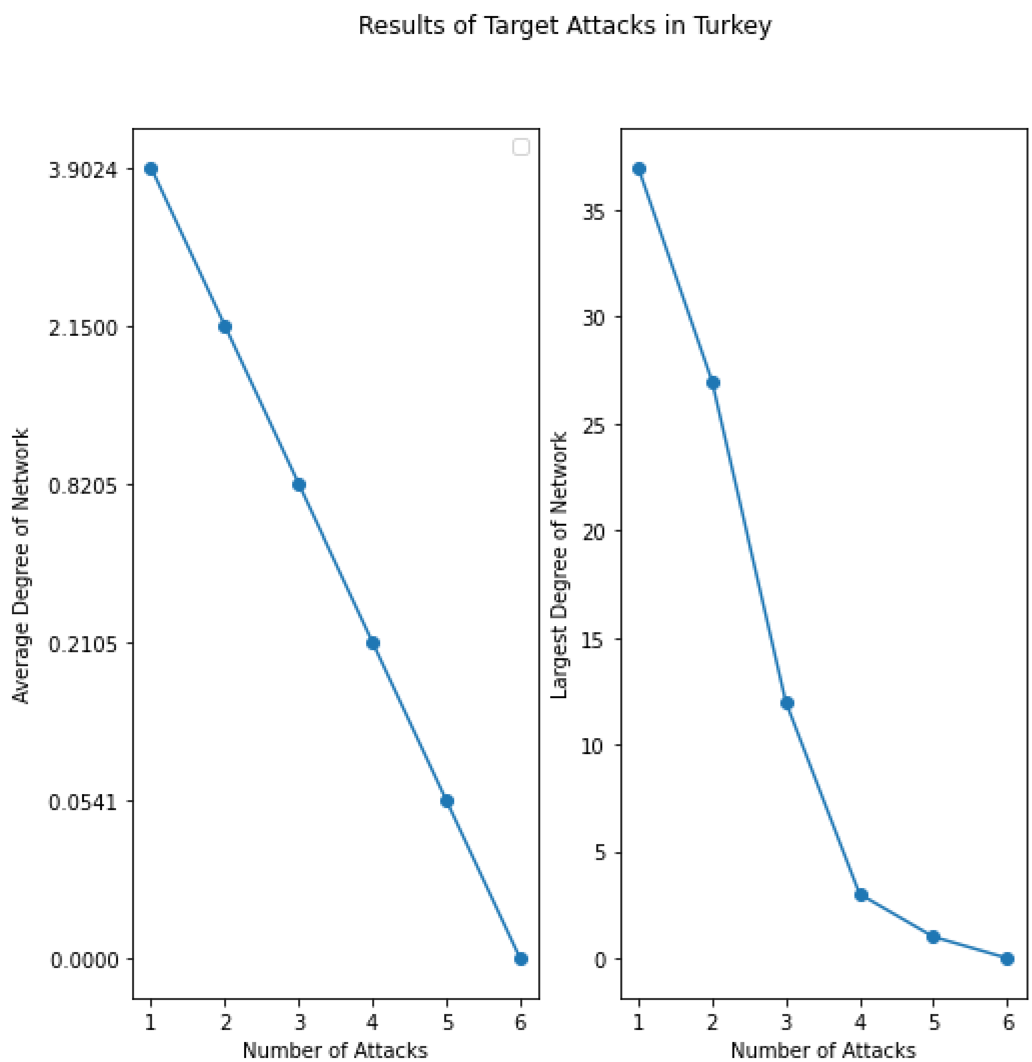

Figure 4.4: Targeted Attacks Results on Turkey's Air Transport Network

In Figure 4.5, the results of the targeted attacks on "***USA's Network***" can be observed. As it is stated on the part 3.3.1, targeted attacks will step by step remove the most critical city and continue until there are no more routes left. As it is with Turkey's network, the change in average degree in the network is on the left side of the figure while the change in the largest degree of the network can be observed on the right of the figure. In each removal, as expected these two measurement metrics keep decreasing. The crucial difference in USA's network is the percentage of cities necessary to remove from the network in order to achieve full collapse. Initially, USA's air transport network had 528 cities and 2559 routes in between them and in order to remove all the edges in the network, 369 cities were needed to be removed. After the removal of this much city, the network completely collapsed. In case of a terrorist attack for example, attacking 70% of the network is necessary.

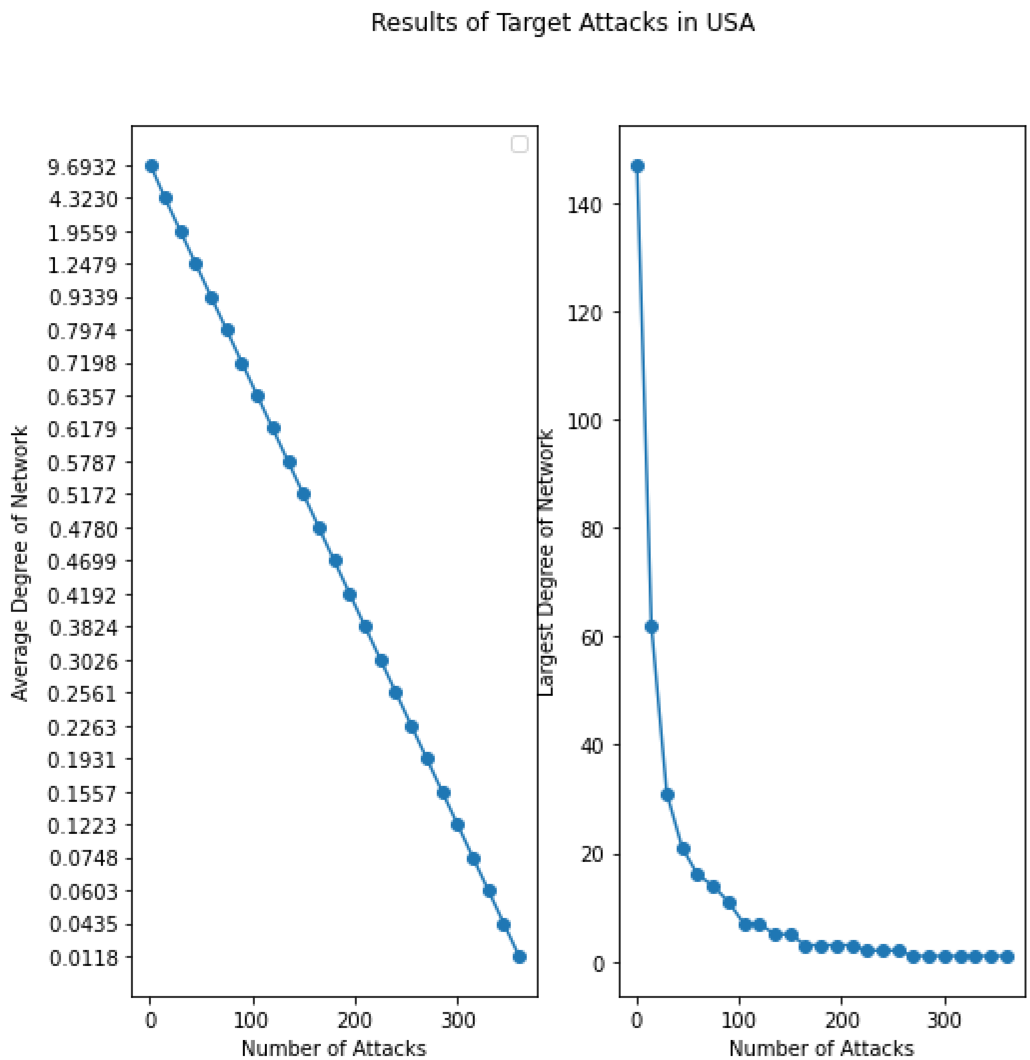

Figure 4.5: Targeted Attacks Results on USA's Air Transport Network

In Figure 4.6, the results of the targeted attacks on "***China's Network***" can be observed. As it is stated on the part 3.3.1, targeted attacks will step by step remove the most critical city and continue until there are no more routes left. As it is with Turkey's network, the change in average degree in the network is on the left side of the figure while the change in the largest degree of the network can be observed on the right side of the figure. In each removal, as expected these two measurement metrics keep decreasing. Again, the crucial difference in China's network is the percentage of cities necessary to remove from the network in order to achieve full collapse. Initially, China's air transport network had 173 cities and 1294 routes in between them and in order to remove all the edges in the network, 122 cities were needed to be removed. After the removal of this much city, the network completely collapsed. In case of a terrorist attack for example, attacking 71% of the network is necessary.

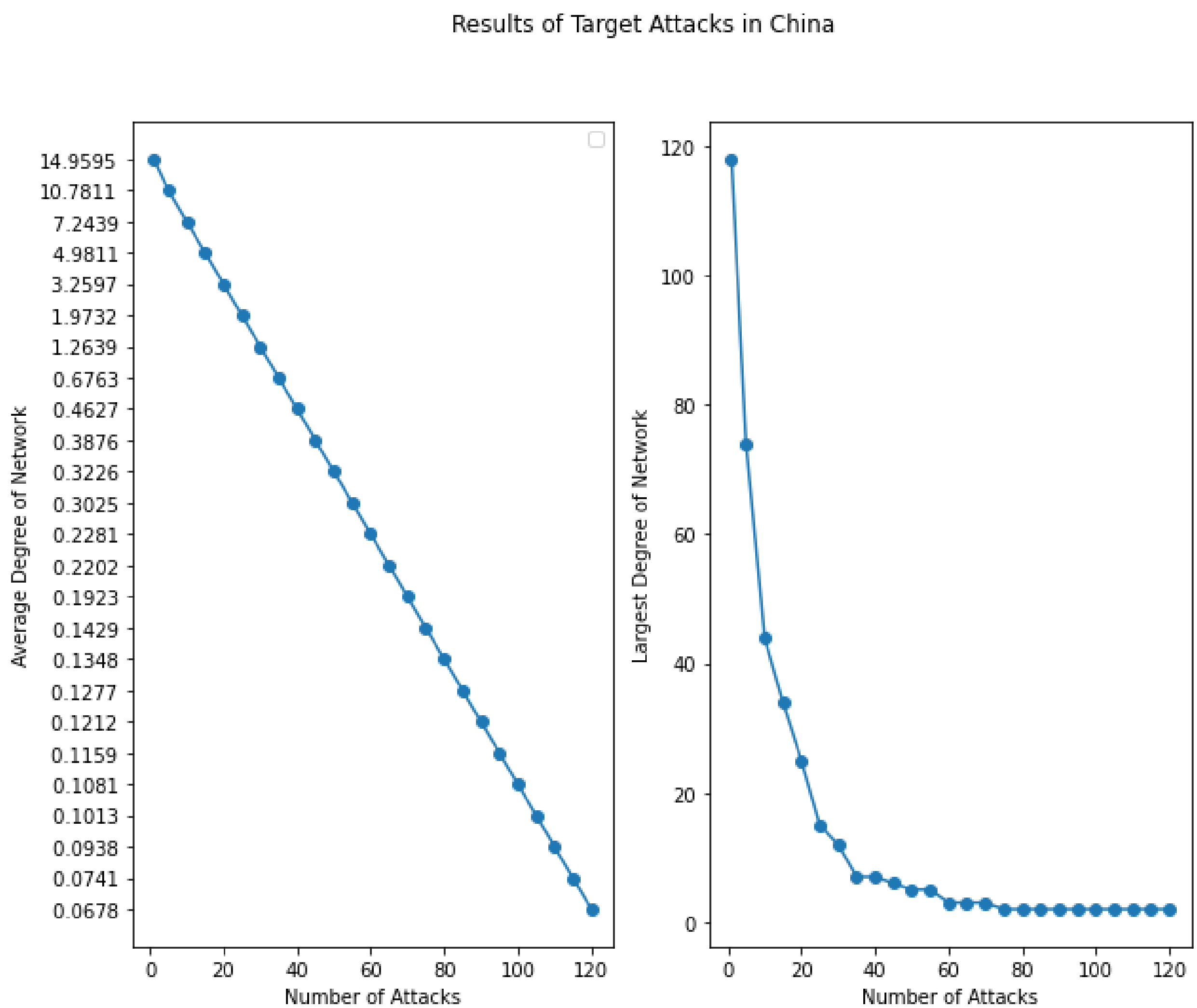

Figure 4.6: Targeted Attacks Results on China's Air Transport Network

5. Conclusion and Discussion

To investigate the effects of failures such as weather conditions, airline traffic delays occurring in airports of any city or much more targeted incidents like a terrorist attack causing huge impact; two different attack types have been introduced; random attacks which removes airports randomly and targeted attacks which removes airports according to their degree, betweenness-centrality, closeness-centrality, in short according to their criticality. After the simulations, in order to measure the results of these events, different measurement metrics are introduced such as largest connected components and global efficiency for the networks tested with random attacks. For the networks tested with targeted attacks, introduced measurement metrics are average degree of the network and largest degree of the network. In the light of all these different measurement metrics, countries' air transport networks are observed and how resistant they are is presented. The larger networks such as the USA's and China’s were much more resistant against both types of attacks while a rather small network like Turkey’s - in terms of its number of airports and routes - was much more vulnerable to both attack types. In Figure 4.1, major three cities, Istanbul, Ankara and Izmir were dropped from the networks separately in random attacks and already the network took a huge blow. In targeted attacks, only the removal of Istanbul, Ankara, Izmir, Adana and Trabzon were enough to collapse the network. This many cities creates only 12% of the whole network. This number is 70% in USA's network and 71% in China's network. The reason for this difference between large and small networks is that larger networks have much more alternatives and the load of the networks is spread over a number of cities. In contrast smaller networks only relay to some certain cities and with the removal of them, routes on the network can not be redirected towards other cities quite easily. Also because of this lack of alternatives and the importance of those three cities in Turkey’s network, after their unavailability much of Turkey’s network - especially eastern parts - became unreachable. Both transportation and economic infrastructural damage that a country may experience because of these disconnections are huge and in order to prevent this possibility more airports and routes should be constructed. In the process of this construction, the aim must be to spread the load of the network through the country as best as it could be and increase the percentage of cities needed for targeted attack for example. In this way, robustness and efficiency may be increased.

6. Appendix

a. Countries Air Transport Network

source_airport_iata	destination_airport_iata	source_airport_name	source_aiport_city	destination_airport_name	destination_aiport_city
ADQ	KLN	Kodiak Airport	Kodiak	Larsen Bay Airport	Larsen Bay
KLN	KYK	Larsen Bay Airport	Larsen Bay	Karluk Airport	Karluk
BRL	ORD	Southeast Iowa Regional Airport	Burlington	Chicago O'Hare International Airport	Chicago
BRL	STL	Southeast Iowa Regional Airport	Burlington	St Louis Lambert International Airport	St. Louis
DEC	ORD	Decatur Airport	Decatur	Chicago O'Hare International Airport	Chicago
DEC	STL	Decatur Airport	Decatur	St Louis Lambert International Airport	St. Louis
JBR	STL	Jonesboro Municipal Airport	Jonesboro	St Louis Lambert International Airport	St. Louis
ORD	BRL	Chicago O'Hare International Airport	Chicago	Southeast Iowa Regional Airport	Burlington
ORD	DEC	Chicago O'Hare International Airport	Chicago	Decatur Airport	Decatur
STL	BRL	St Louis Lambert International Airport	St. Louis	Southeast Iowa Regional Airport	Burlington
STL	DEC	St Louis Lambert International Airport	St. Louis	Decatur Airport	Decatur
STL	JBR	St Louis Lambert International Airport	St. Louis	Jonesboro Municipal Airport	Jonesboro
KTN	MTM	Ketchikan International Airport	Ketchikan	Metlakatla Seaplane Base	Metakatla
MTM	KTN	Metlakatla Seaplane Base	Metakatla	Ketchikan International Airport	Ketchikan
ATL	LWB	Hartsfield Jackson Atlanta International Airport	Atlanta	Greenbrier Valley Airport	Lewisburg

Table a-1: American Air Transport Network

source_airport_iata	destination_airport_iata	source_airport_name	source_aiport_city	destination_airport_name	destination_aiport_city
BHY	XIY	Beihai Airport	Beihai	Xi'an Xianyang International Airport	Xi'an
CAN	CKG	Guangzhou Baiyun International Airport	Guangzhou	Chongqing Jiangbei International Airport	Chongqing
CAN	CTU	Guangzhou Baiyun International Airport	Guangzhou	Chengdu Shuangliu International Airport	Chengdu
CGO	CGQ	Zhengzhou Xinzheng International Airport	Zhengzhou	Longjia Airport	Changchun
CGO	CKG	Zhengzhou Xinzheng International Airport	Zhengzhou	Chongqing Jiangbei International Airport	Chongqing
CGO	CTU	Zhengzhou Xinzheng International Airport	Zhengzhou	Chengdu Shuangliu International Airport	Chengdu
CGO	HGH	Zhengzhou Xinzheng International Airport	Zhengzhou	Hangzhou Xiaoshan International Airport	Hangzhou
CGO	HRB	Zhengzhou Xinzheng International Airport	Zhengzhou	Taiping Airport	Harbin
CGO	KMG	Zhengzhou Xinzheng International Airport	Zhengzhou	Kunming Changshui International Airport	Kunming
CGO	URC	Zhengzhou Xinzheng International Airport	Zhengzhou	Ürümqi Diwopu International Airport	Urumqi
CGQ	CGO	Longjia Airport	Changchun	Zhengzhou Xinzheng International Airport	Zhengzhou
CGQ	NKG	Longjia Airport	Changchun	Nanjing Lukou Airport	Nanjing
CGQ	TNA	Longjia Airport	Changchun	Yaoqiang Airport	Jinan
CGQ	TSN	Longjia Airport	Changchun	Tianjin Binhai International Airport	Tianjin
CKG	CAN	Chongqing Jiangbei International Airport	Chongqing	Guangzhou Baiyun International Airport	Guangzhou

Table a-2: China Air Transport Network

b. Countries Air Transport Network Representation on Gephi

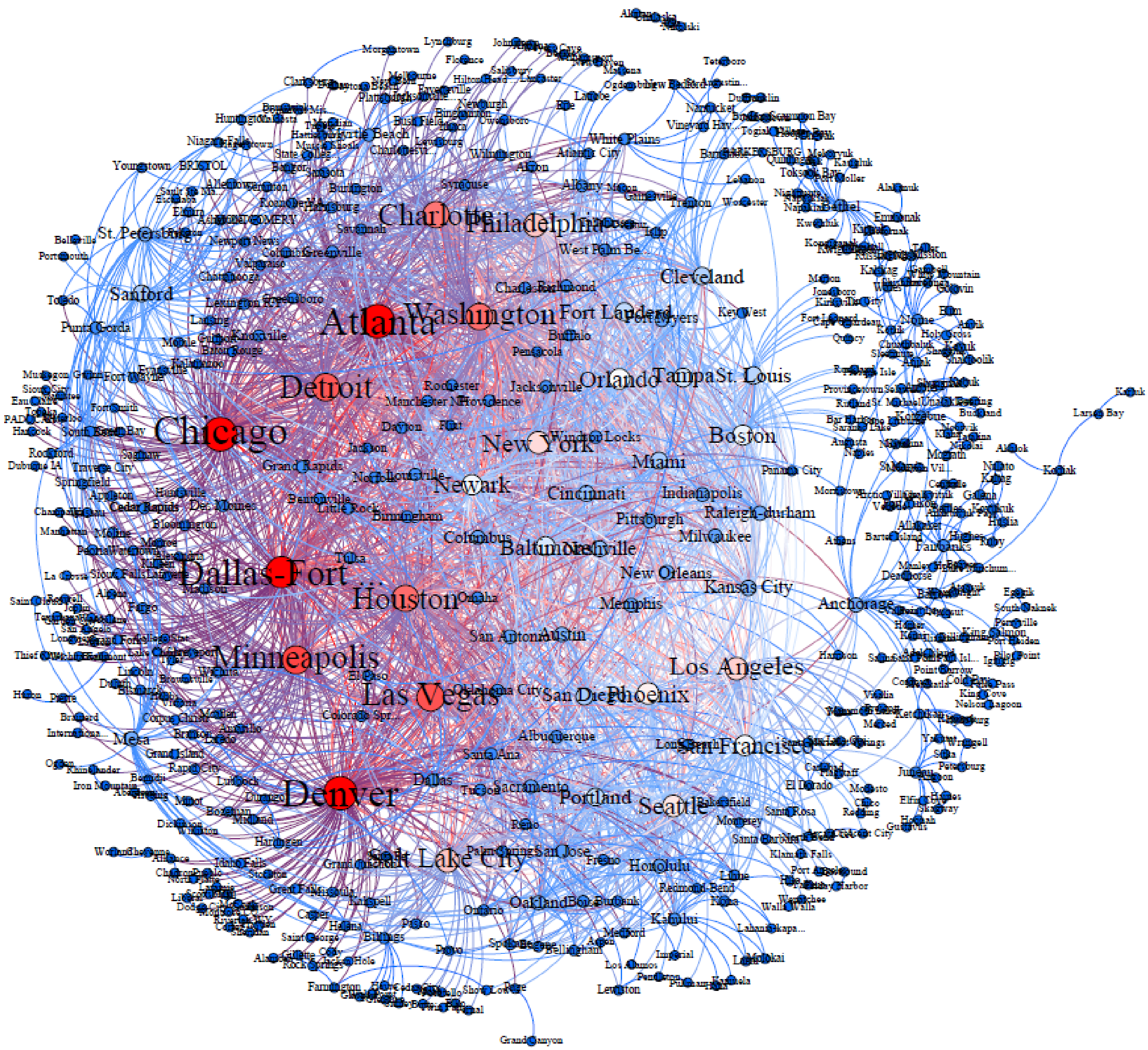

Figure b-1: United State of America's Air Transport Network Representation on Gephi

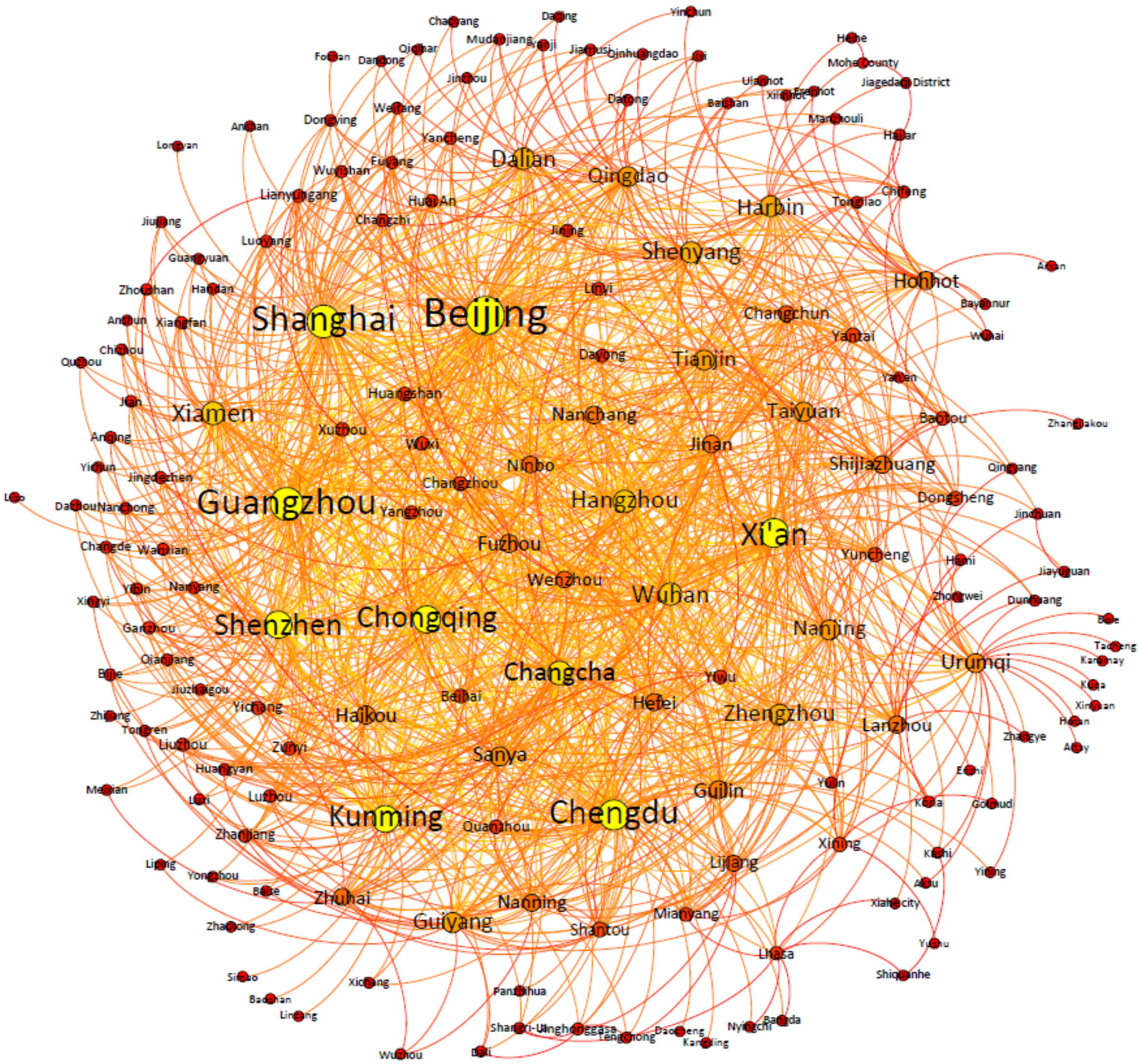

Figure b-2: China's Air Transport Network Representation on Gephi

c. Criticality Measurements of The Airports

	Degree	Betweenness Centrality	Closeness Centrality
Chicago	147	0.129503	0.505385
Atlanta	145	0.078457	0.460951
Denver	145	0.154847	0.505878
Dallas-Fort Worth	132	0.080282	0.454891
Minneapolis	113	0.081678	0.488269
Las Vegas	110	0.063124	0.488729
Detroit	109	0.034794	0.445138
Houston	104	0.034541	0.442859
Washington	104	0.047841	0.443995
Charlotte	102	0.036522	0.442481
Salt Lake City	84	0.059370	0.472275
Philadelphia	84	0.022465	0.434699
Los Angeles	81	0.051801	0.472705
New York	79	0.006877	0.433972
Seattle	76	0.135238	0.482370

Table c-1: USA's cities criticality measurements

	Degree	Betweenness Centrality	Closeness Centrality
Beijing	118	0.223923	0.757709
Guangzhou	94	0.094852	0.682540
Shanghai	94	0.096039	0.685259
Chengdu	83	0.116155	0.659004
Xi'an	78	0.082435	0.646617
Shenzhen	71	0.035985	0.620939
Chongqing	71	0.049386	0.623188
Kunming	69	0.072188	0.601399
Changcha	57	0.019439	0.595156
Xiamen	53	0.012532	0.565789
Wuhan	51	0.020899	0.583051
Hangzhou	51	0.018365	0.581081
Dalian	47	0.019616	0.549521
Shenyang	46	0.012293	0.546032
Zhengzhou	45	0.008388	0.567657

Table c-2: China's cities criticality measurements

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